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Automated Classification between Age-related Macular Degeneration and Diabetic Macular Edema in OCT Image Using Image Segmentation

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***Abstract*—Age-related macular degeneration (AMD) and Diabetic macular edema (DME) are to lead causes to make a visual loss in people. People are suffered from the use of many time to diagnose and to wait for treatment both of diseases. This paper proposes a step of image segmentation to be divided the optical coherence tomography (OCT) to find the retinal pigment epithelium (RPE) layer and to detect a shape of drusen in RPE layer. Then, the RPE layer is used for finding retinal nerve fiber layer (RNFL) and for detecting a bubble of blood area in RNFL complex. Finally, this method uses a binary classification to classify two diseases characteristic between AMD and DME. We use 16 OCT images of a case study to segmentation and classify two diseases. In the experimental results, 10 images of AMD and 6 images of DME can be detected and classified to accuracy of 87.5%.**

Keywords—optical coherence tomography; OCT; age-related macular degeneration; AMD; diabetic macular edema; DME; image segmentation; classification

I. INTRODUCTION

Optical coherence tomography (OCT) is a clinical image [1] have been used to visualize the eye to use to observe and track a develop disease. OCT is a high resolution cross-sectional image [2] of layers of biological tissues (Fig.1). In the clinical can use OCT image to indicate an eye disease.

Age-related macular degeneration (AMD) is a degeneration of the eye. AMD is the leading cause of sever visual impairment and visual loss. In United State have the AMD patient estimated 8 million persons, have monocular AMD and binocular AMD [3, 4]. Person at least 55 year old. Most case, the clinical finding is the presence of drusen (Fig.2a). Drusen is an abnormality between the basal lamina of retinal pigment epithelium (RPE) and the inner collagenous layer of Bruch's membrane.

Diabetic macular edema (DME) is a blood leakage pass the RPE layer and photoreceptor inner/outer segment (IS/OS) from choroid into the RNFL complex [5, 6]. And the visual has loss by the area of blood or bubble in RNFL complex. In United State have the DME patient estimated 26 million persons. In the clinical using OCT to finding is the presence of blood area or bubble (Fig.2b). Blood area or bubble is presence in the RNFL complex [7].

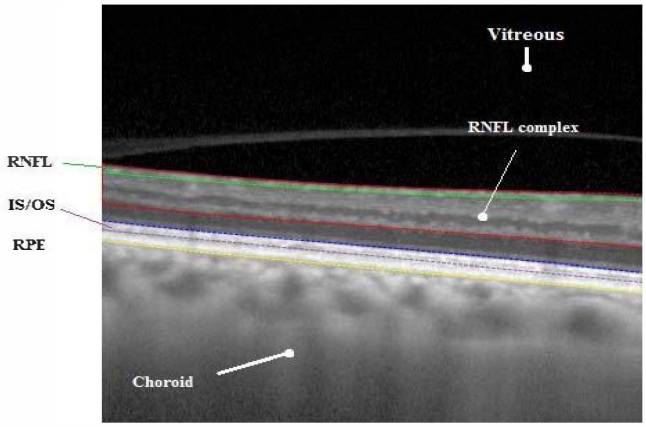

Fig. 1. Traget retinal layers of a cross-sectional OCT image. RNFL: retinal nerve fiber layer; IS/OS: photoreceptor inner/outer segment; RPE: retinal pigment epithelium; RNFL complex is indicated by the red dotted region.

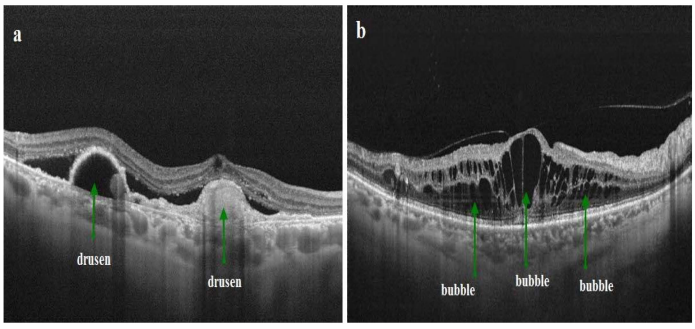

Fig. 2. Drusen of AMD in RPE layer(a). blood area or bubble of DME in RNFL complex.

Recently, have many people in many area are to be disease and the clinical is least of technician or doctor to treatment many people in short time. This paper use to help clinical to a

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primary identification a disease using OCT image. And OCT image structure can use to identify more of eye disease but in this paper we focus in a leading of visual loss to help a partial quickly to be treated it.

II. Materials and Methodology

The images were acquired form optical website in the OCT image. Examples in Fig. 3.

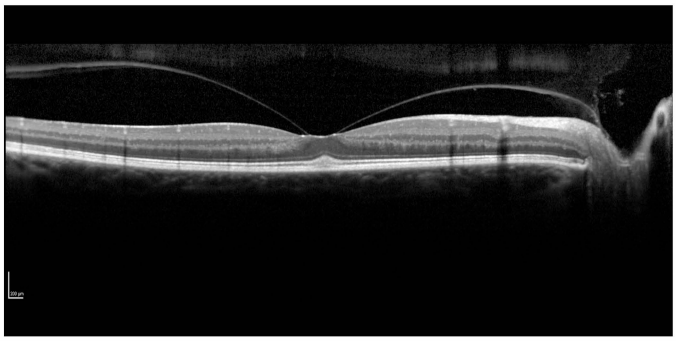

Fig. 3. Example of cross-sectional image

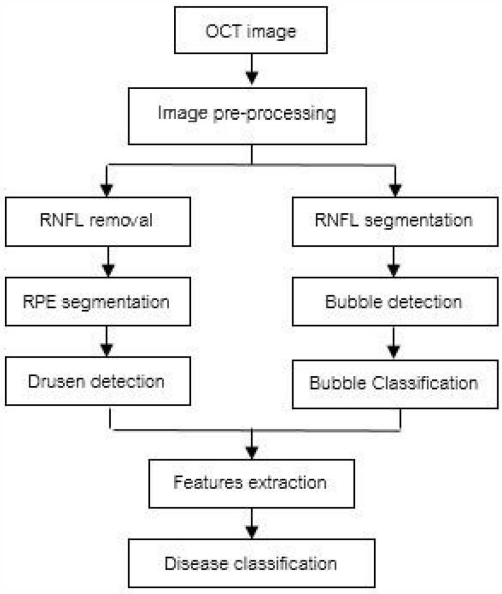

Fig. 4. Flowchart of the classification method.

A. Image pre-processing

Modified image with the filtering algorithm is used to reduce noise in facilitate the AMD segmentation process and DME segmentation process. Because in RPE layer and RNFL layer segmentation, noise removal is needed. In this paper, we use a Gaussian filter to reduce noise.

B. RNFL removal, RPE segmentation

Propose of removing the high pixel in RNFL complex is to facilitate RPE layer segmentation. Because the pixel of the background is similar throughout image.

The RPE layer is high pixel value in OCT image, show in Fig. 4. Threshold can be used to (Fig. 4) identify it. And next step, we represent an original RPE layer without high pixel of RNFL complex (Fig. 5) with an estimate line value of PRE (ELPRE).

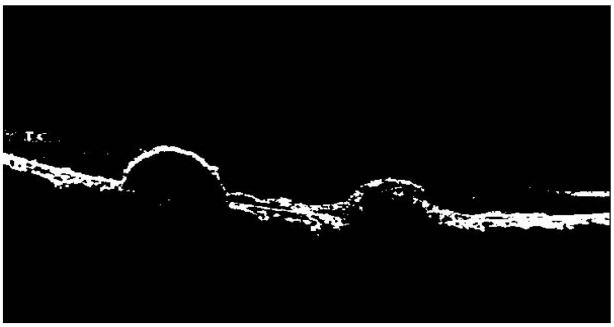

Fig. 5. Result of RPE segmentation.

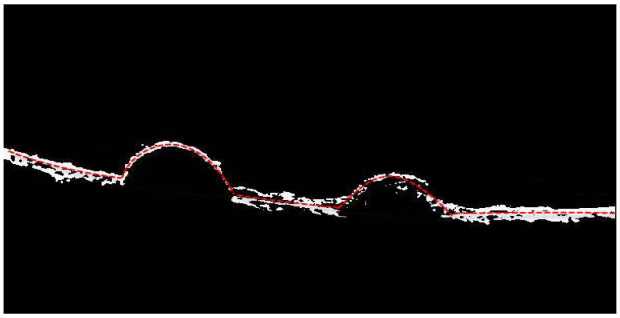

Fig. 6. Result of RNFL removal and estimate line value of PRE (ELRPE) by the red dot line.

C. Drusen detection

Propose the process to use an estimate line value of PRE to help to drusen detection. The drusen is a shape of abnormality in RPE layer. This step we enchant image form Fig. 5 to clearly the RPE layer and find mean point between a top and bottom white pixel in every column of image and then make a new estimate line by mean (Fig. 6). Then make a new estimate line under the drusen with calculate by corners in each drusen and combine an estimate line value of PRE and a new estimate line of PRE, then detect shape of drusen between both lines (Fig. 7).

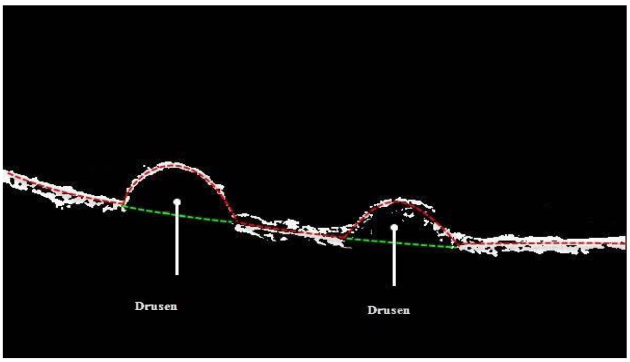

Fig. 7. Result of Drusen detection using combinetion of ELPRE and new estimate line of PRE(NEPRE)

D. RNFL segmentation, Bubble detection

Propose the step to segmentation RNFL complex. We use threshold to find a RNFL complex but the result is has both of RNFL and RPE, then we use RPE layer in RPE segmentation step to erase in result (Fig. 8). The result has RNFL complex and some IS/OS layer, then we use image segmentation find the bubble in RNFL complex [8, 9], show in Fig. 9.

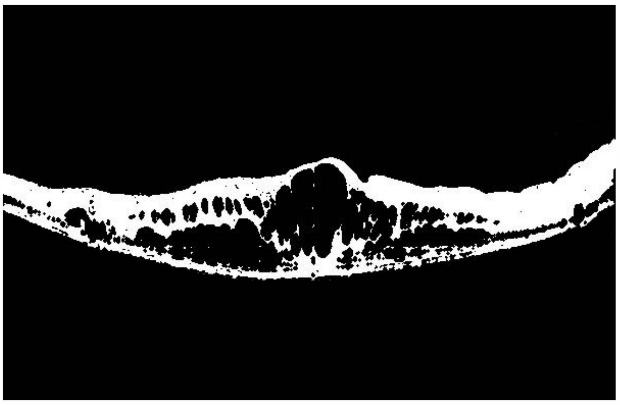

Fig. 8. Result of final RNFL segmentation

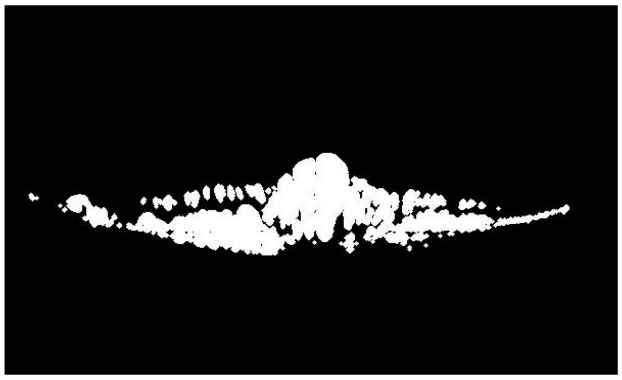

Fig. 9. Result of bubble detection

E. Bubble classification

Process to classification of bubble in RNFL complex and other such as in IS/OS layer. Because bubble in IS/OS layer has chance to be AMD is not DME. We use RPE layer to classification the IS/OS bubble cause of IS/OS layer is adjoin RPE layer. Then compute upper RPE layer area about 10 – 15 pixel if find a bubble we can classification this bubble is not in RNFL complex.

F. Feature extractiong

Process of collect a feature form image segmentation step to use to classification eye diseases between AMD and DME. The feature. Because both of disease have a different characteristic. In this step we propose a characteristic of both disease to collect to use to classify.

- RPEA prefer of an abnormality of RPE layer. Collect in binary value between 0 and 1. 0 is normality RPE layer, 1 is abnormality RPE layer.
- RNFLA prefer of bubble in RNFL complex region. Collect in binary value between 0 and 1. 0 is has bubble upper RPE layer, 1 is has not bubble upper RPE layer.
- AOB prefer of bubble outer RNFL region near RPE layer. Collect in binary value between 0 and 1. 0 is the bubble is upper RPE layer and in IS/OS layer, 1 is else.

G. Disease classification

Propose an algorithm to use data from feature extraction to classification by binary classification algorithm [10, 11]. AMD and DME is has a different characteristic, binary classification is simple and easy to classified this problem. Show in Fig. 10. If PREA is 0 prefer of PRE is normality and this case can be an DME or normal retina else if RPE is 1 prefer of PRE is abnormality and this case can be AMD but must look for Area of bubble, if AOB is upper the drusen and bubble adjoin the RPE layer this case can be DME.

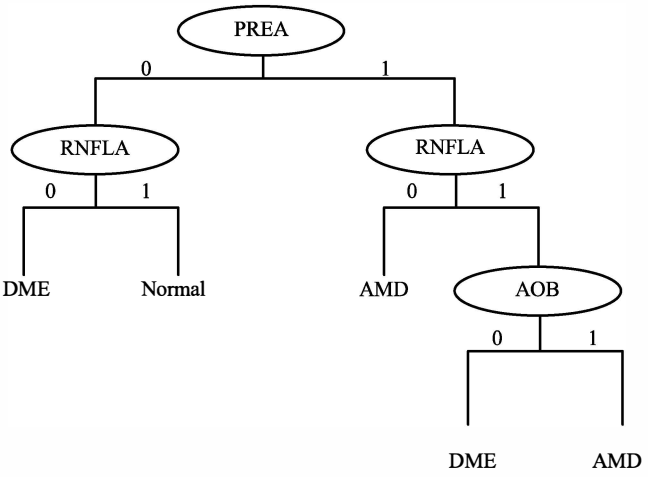

Fig. 10. Binary classification of AMD and DME classification

III. RESULT

The proposed segmentation is applied to unseen image. And can classify in both disease. Show in Fig. 11. This algorithm can find the bubble of DME 149 bubble form 172 in 6 DME images and can find drusen area of AMD 16 from 16 drusens in 10 AMD images and 100% to classification between AMD and DME disease. But this algorithm can't use with the convert of color source image because the color image has more noises, the Gaussian filter is not enough for reduce noise. Show in Fig. 12. In this result show bubble detection in DME the algorithm can detection all of bubble but this has less shape detection.

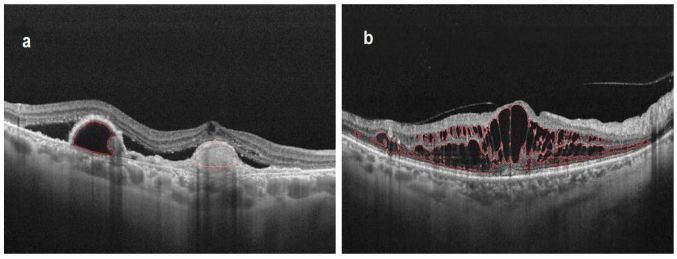

Fig. 11. Result of AMD detection (a) and DME detection (b)

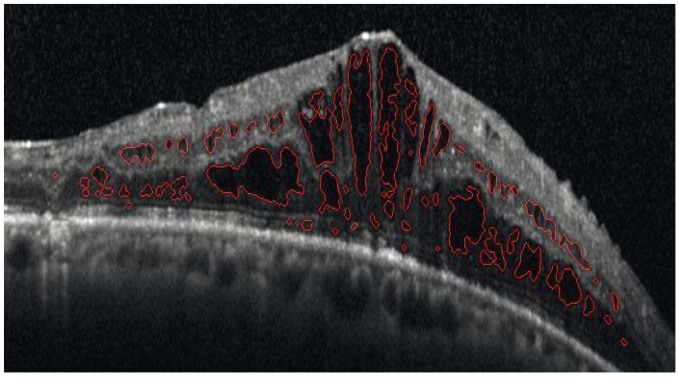

Fig. 12. The result convert form color source image.

IV. CONCLUSION

The process use a normal image segmentation to classification an abnormality disease in retinal such as AMD and DME for OCT image. Results demonstration that the method was able to segmentation and classification a drusen and bubble. May be in future the clinical can useful to primary identification in partial to faster pursue and treatment.

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